HAR - HUMAN ACTIVITY RECOGNITION

Project Report

Group Members

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1. Overview:

Mobile devices are becoming increasingly sophisticated, and the latest generation of smart cell phones now incorporates many diverse and powerful sensors. These sensors include GPS sensors, vision sensors (i.e., cameras), audio sensors (i.e., microphones), light sensors, temperature sensors, direction sensors (i.e., magnetic compasses), and acceleration sensors (i.e., accelerometers). The availability of these sensors in mass-marketed communication devices creates exciting new opportunities for data mining and data mining applications [1]. The availability of diverse and powerful sensors in smart cell phones is highly valuable for Human Activity Recognition (HAR) by enabling the acquisition of useful information.

Did you ever wonder what your smartphone knows about you? Or how it learns about you? Wouldn't it be great if it could tell you things that you don't even recognize about how you walk, talk and act? Smartphones are already capable of doing this, and many researchers are dedicated to finding ways to gather and interpret the most useful information.

In this Project, we have studied an open-source dataset. In our study, we have conducted data exploration, activity exploration, participant exploration, and personal information exploration analysis to collect valuable insights into human activity recognition.

2. Introduction to HAR:

Human Activity Recognition (HAR) is a field of study and technology focused on identifying and classifying the physical activities and actions of individuals based on data collected from various sensors. The goal of HAR is to automatically determine what activity a person is performing at any given time, such as walking, running, sitting, standing, cycling, or more complex activities like cooking or exercising.

2.1 Applications of HAR:

Human Activity Recognition has a wide range of applications, some of which are listed here:

- **Health and Fitness Monitoring**: Tracking physical activity levels, identifying sedentary behavior, and providing personalized fitness recommendations. [2]

- **Elderly Care:** Monitoring the daily activities of elderly individuals to detect falls or abnormal behavior.
- **Smart Homes:** Enhancing home automation systems by recognizing the activities of residents and adjusting the environment accordingly.
- **Workplace Safety:** Monitoring workers' activities to ensure compliance with safety protocols and prevent accidents.
- **Rehabilitation:** Assisting in physical therapy and rehabilitation by tracking progress and ensuring adherence to prescribed exercises.

  For more and detailed applications of HAR we can refer to [2].

3. Methodology:

A set of trials with volunteers was required to create and develop the human activity recognition dataset. In total, 30 people with ages from 19 to 48 years participated in this research and performed a set of motion sequences comprising the 6 proposed ADL (standing, sitting, laying, walking, walking upstairs and walking downstairs). Each subject performed the experiment protocol twice, and each activity was at least performed two times on each trial to simulate repeatability. [3]

The experiments have been video-recorded to facilitate the data labeling. The obtained database has been randomly partitioned into two sets, where 70% of the patterns has been used for training purposes and 30% as test data.[4]

For AR purposes, we have developed a smartphone application based on the Google Android Operating System. The recognition process starts with the acquisition of the sensor signals, which are subsequently pre-processed by applying noise filters and then sampled in fixed-width sliding windows of 2.56 sec and 50% overlap. From each window, a vector of 17 features is obtained by calculating variables from the accelerometer signals in the time and frequency domain(e.g. mean, standard deviation, signal magnitude area, entropy, signal-pair correlation, etc.) [4]

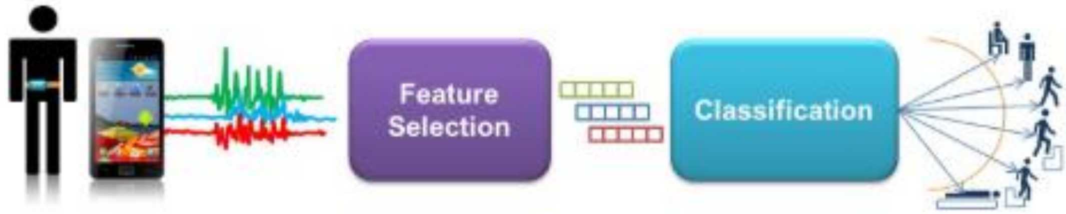


Figure 1: AR Process
Image source [4]

Finally, these patterns are used as input of the trained SVM Classifier for the recognition of the activities [4]. The entire AR process pipeline is as shown in Figure 1.

4. Data Exploration:

4.1 Which features are there?

The features seem to have a main name and some information on how they have been computed attached. Grouping the main names will reduce the dimensions for the first impression.

Mainly there are 'acceleration' and 'gyroscope' features. A few 'gravity' features are there as well. It's impressive how many features there are in regard of the limited number of sensors used.

	count
fBodyAcc	79
fBodyGyro	79
fBodyAccJerk	79
tGravityAcc	40
tBodyAcc	40
tBodyGyroJerk	40
tBodyGyro	40
tBodyAccJerk	40
tBodyAccMag	13
tGravityAccMag	13
tBodyAccJerkMag	13
tBodyGyroMag	13
tBodyGyroJerkMag	13
fBodyAccMag	13
fBodyBodyAccJerkMag	13
fBodyBodyGyroMag	13
fBodyBodyGyroJerkMag	13
angle	7
subject	1
Data	1

4.2 What types of data are there?

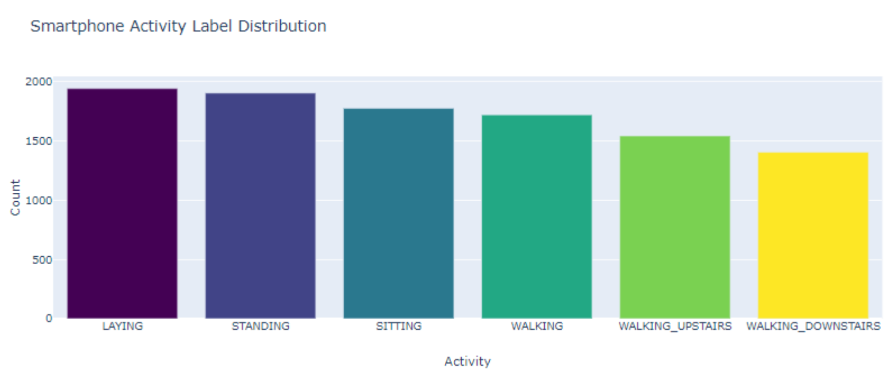
Except for the label and the newly created 'Data' and 'subject' features there is only numerical data. Fortunately, there are no missing values.

```
Null Values In DataFrame: 0

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10299 entries, 0 to 10298
Columns: 563 entries, tBodyAcc-mean()-X to Data
dtypes: float64(561), object(2)
memory usage: 44.2+ MB
```

4.3 How are the labels distributed?

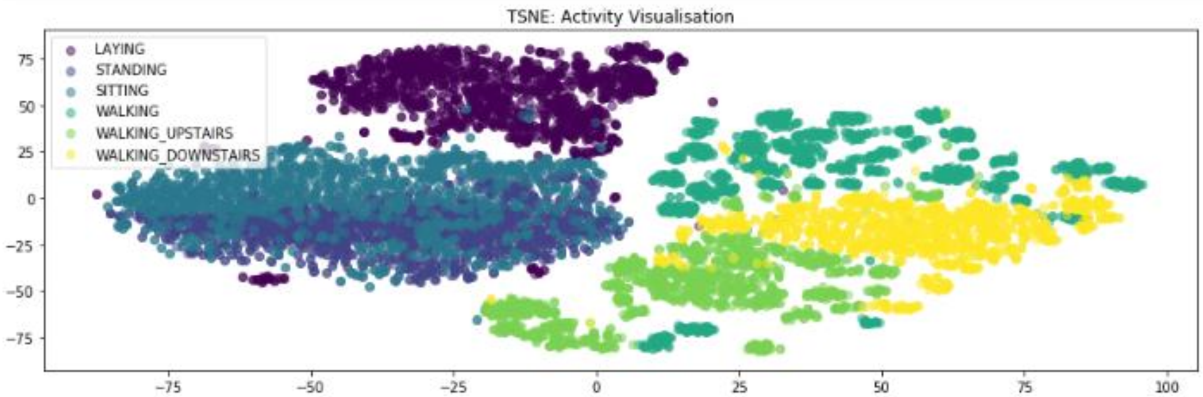
Although there are fluctuations in the label counts, the labels are quite equally distributed.
Assuming the participants had to walk the same number of stairs upwards as well as downwards and knowing the smartphones had a constant sampling rate, there should be the same amount of datapoints for walking upstairs and downstairs. Disregarding the possibility of flawed data, the participants seem to walk roughly 10% faster downwards.

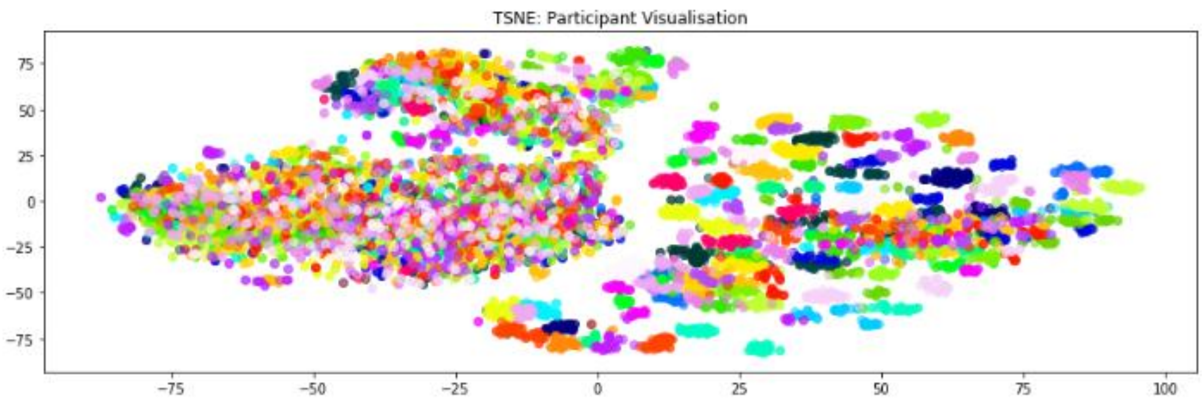


5. Activity Exploration:

5.1 Are the activities separable?

In plot 1 you can clearly see the activities are mostly separable. Plot 2 reveals personal information of the participants. Everybody has for example a unique/sparable walking style (on the upper right). Therefore, the smartphone should be able to detect what you are doing and who is using the smartphone (if you are moving around with it).





5.2 How good are the activities separable?

With a basic untuned model the activity of the smartphone user can be predicted with an accuracy of 95%. This is pretty striking regarding six equally distributed labels. If the smartphone or an App wants to know what you are doing, this is feasible.

```
Accuracy on testset:    0.9553
```

6. Participant Exploration:

6.1 How good are the participants separable?

Detecting the correct participant regarding their current activity is not alone possible but astonishing accurate regarding the 30 different persons (94% by walking style).

Noticeable is that the accuracy seems to rise if the participant moves around. This implies a unique walking/movement style for each person.

```
Activity: LAYING
Accuracy on testset:    0.6481

Activity: STANDING
Accuracy on testset:    0.5493

Activity: SITTING
Accuracy on testset:    0.5303

Activity: WALKING
Accuracy on testset:    0.9513

Activity: WALKING_UPSTAIRS
Accuracy on testset:    0.9249

Activity: WALKING_DOWNSTAIRS
Accuracy on testset:    0.9091
```

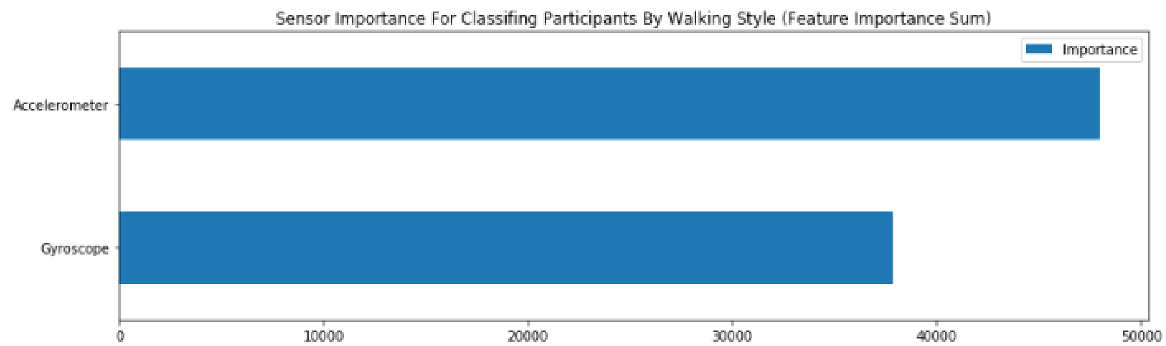
6.2 How Long Does the Smartphone Gather Data for This Accuracy?

The smartphone is quite fast (1 - 1.5 min) in guessing correctly.

Activity	Accuracy	Seconds
LAYING	0.648148	82.944000
STANDING	0.549266	81.322667
SITTING	0.530337	75.818667
WALKING	0.951276	73.472000
WALKING_UPSTAIRS	0.924870	65.877333
WALKING_DOWNSTAIRS	0.909091	59.989333

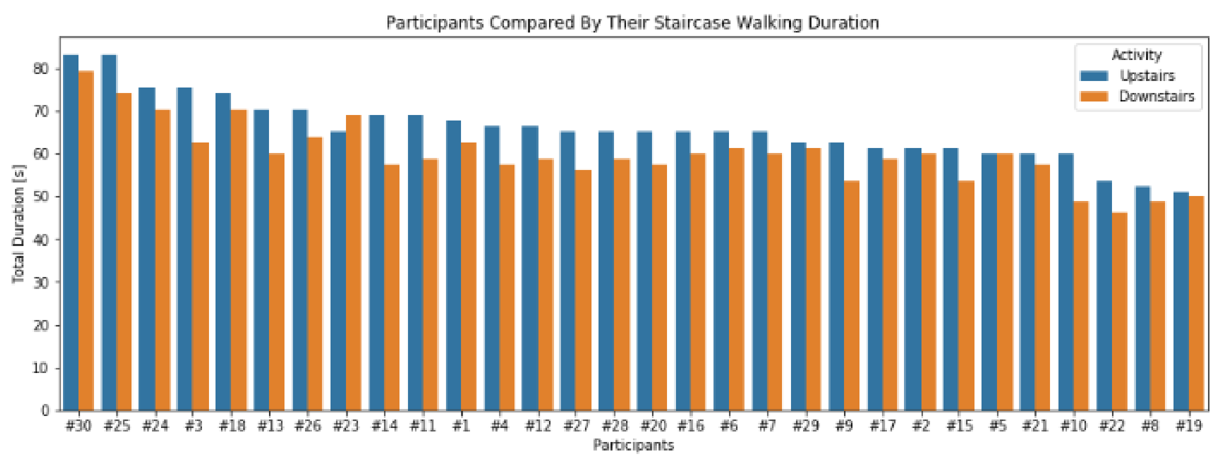
6.3 Which Sensor Is More Important for Classifying Participants by Walking Style?

The accelerometer supplies slightly more information. But both sensors are important for classification and refraining from using both sensors will be a drawback for the quality of the model.



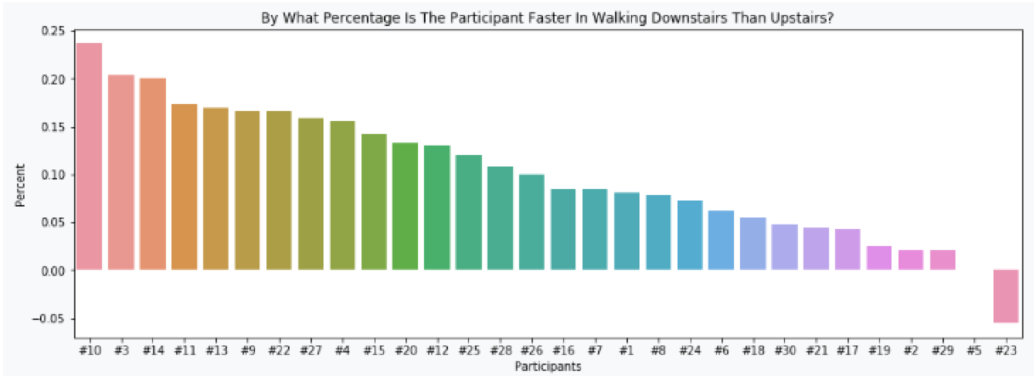
6.4 How Long Does the Participant Use the Staircase?

Nearly all participants have more data for walking upstairs than downstairs. Assuming an equal number of up- and down-walks, the participants need longer walking upstairs. Furthermore, the range of the duration is narrow and adjusted to the conditions. A young person being 50% faster in walking upstairs than an older one is reasonable.



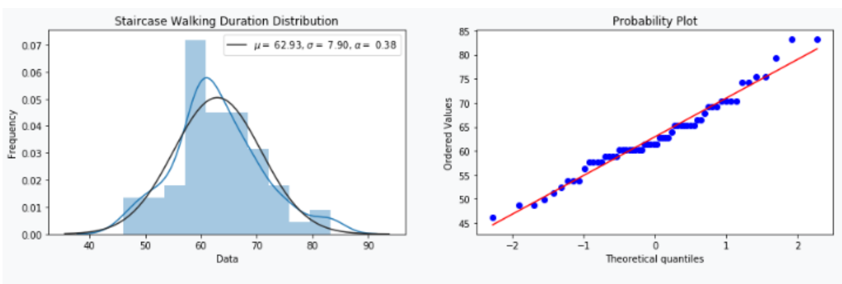
6.5 How Much Does the Up-/Downstairs Ratio Vary?

There is a wide range in between the participants for their ratio of up-/down-walking. Since this represents their physical condition, we can imagine a correlation to their age and health (speculative).



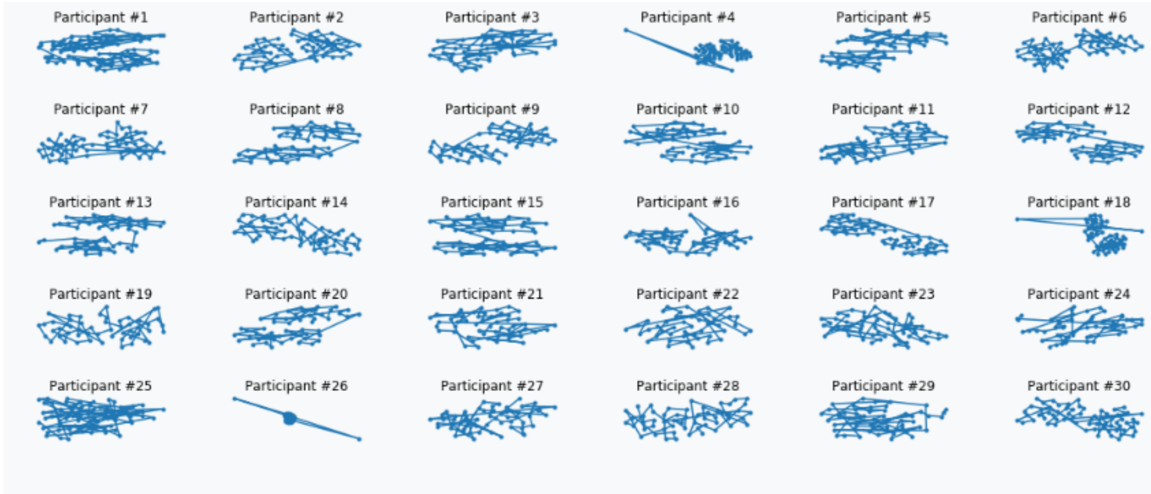
6.6 Are there Conspicuities in the Staircase Walking Duration Distribution?

As expected from most real-world data the duration walking on the staircase is normally distributed.



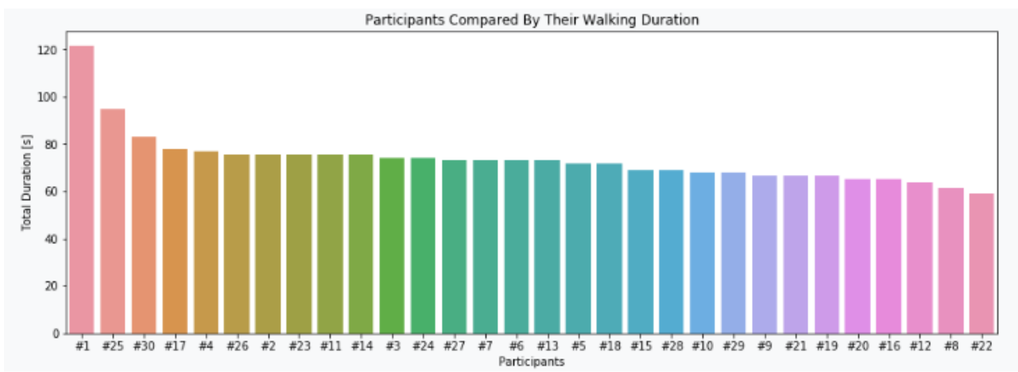
6.7 Is there a Unique Walking Style for Each Participant?

Due to the fact that there is (mostly) only a single connection between the clusters and each cluster has just about the same size we concluded that each cluster represents a single walking experiment.



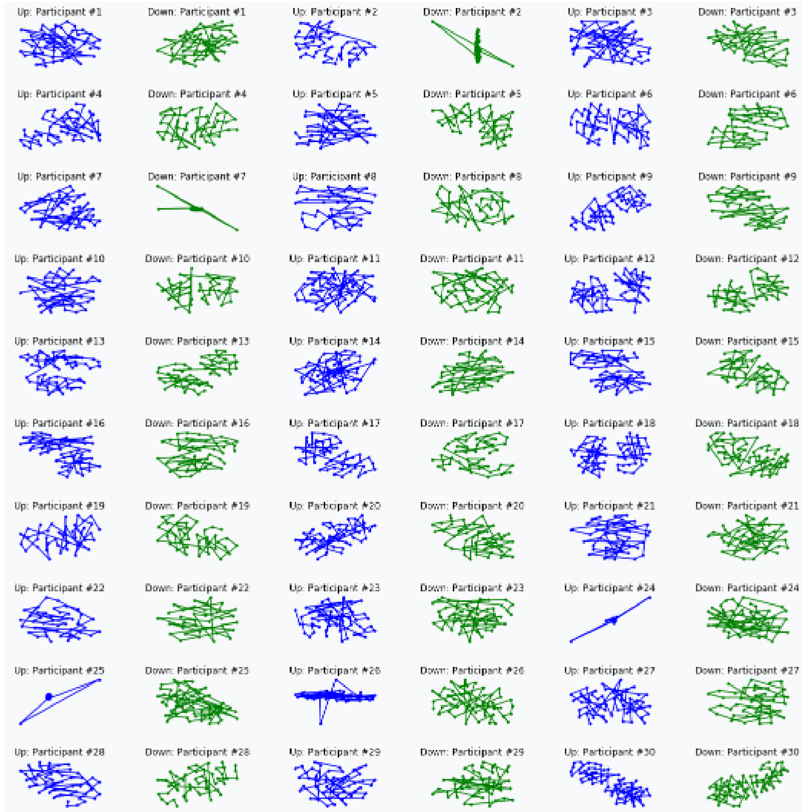
6.8 How Long Does the Participant Walk?

Since the duration of each participant walking is distributed over a range, we assume the participants had a fixed walking distance for their experiment rather than a fixed duration.



6.9 Is there a Unique Staircase Walking Style for Each Participant?

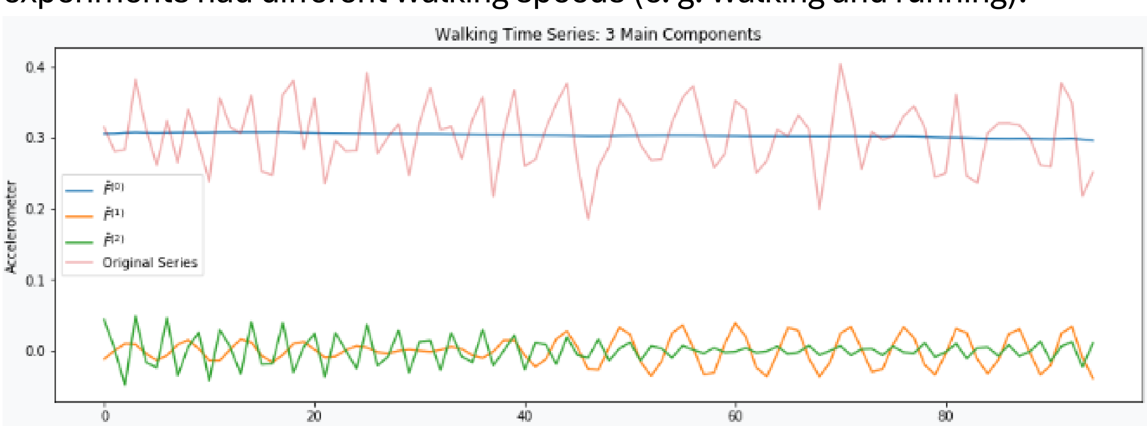
In most of the plots a structure with two clusters is again recognizable. Going up and down the stairs two times is likely for the experiment.



7. Exploring Personal Information:

7.1 What is the Walking Frequency of a Single Participant?

We can see the original data from the accelerometer can be decomposed into three main components. The first one (blue) reveals the overall constant trend. The other two (yellow, green) represent the oscillating walking frequencies. The frequency change in the middle of the plot underlines the assumption of two distinct walking experiments. Furthermore, it can be stated that both experiments had different walking speeds (e. g. walking and running).

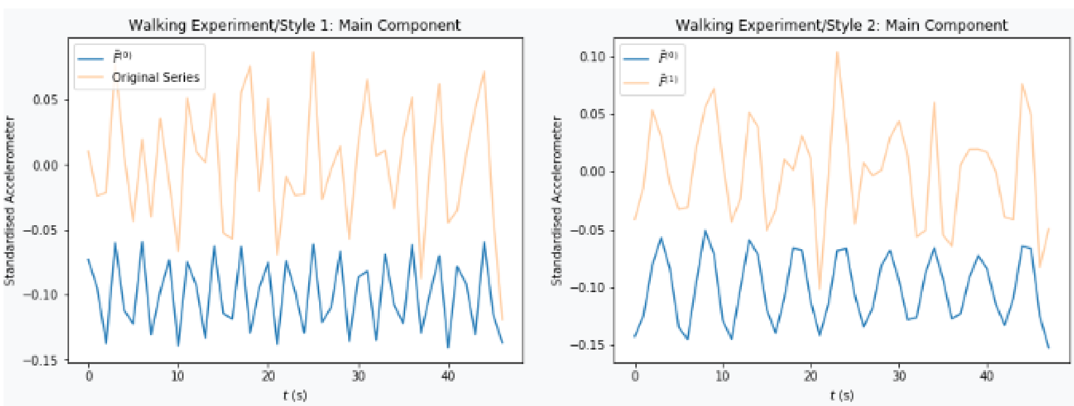


7.2 What Is the Walking Frequency of Both Found Speeds?

Decomposing both experiments separately offers highly improved results. Fitting a sin-curve to the main component should reveal the step frequency of the participant. Fitting a sinus curve to the main component of the walking experiments of participant #1 reveals the computed speed of both experiments differed by a factor of nearly 2.

Since the second speed is suspiciously low there could be a sampling problem and information could have been irrevocably lost while aggregating the dataset. Potentially the datapoints are too widespread to reconstruct the underlying frequency in a correct way.

For the decomposition we have only shown a single participant with the two walking styles. By computing a t-SNE visualization of the walking of all participants you can see two clusters for each participant (Some more distinct than others). Therefore, the option of splitting the styles by decomposition suggests itself.



8. Conclusion:

Within a short time (1-1.5 min) the smartphone has enough data to determine what its user is doing (95%: 6 activities) or who the user is (Walking 94%: 30 participants) and even the basics of a person's specific walking style (Slow steps per second). By linking these insights to more personal data of the participants extensive options open up.

In addition, these insights have been extracted from only two smartphone sensors which probably could be accessed by most of our Apps.

9. References:

1. Jennifer R. Kwapisz, Gary M. Weiss and Samuel A. Moore (2010). Activity Recognition using Cell Phone Accelerometers, ACM SIGKDD Explorations, 12(2):74-82., Washington DC.
2. Jeffrey W. Lockhart, Tony Pulickal, and Gary M. Weiss (2012). Applications of Mobile Activity Recognition, Proceedings of the ACM UbiComp International Workshop on Situation, Activity, and Goal Awareness, Pittsburgh, PA.
3. Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra, Jorge L. Reyes-Ortiz. Energy Efficient Smartphone-Based Activity Recognition using Fixed-Point Arithmetic. Journal of Universal Computer Science. Special Issue in Ambient Assisted Living: Home Care. Volume 19, Issue 9. May 2013.
4. Davide Anguita, Alessandro Ghio, Luca Oneto, Xavier Parra and Jorge L. Reyes-Ortiz. Human Activity Recognition on Smartphones using a Multiclass Hardware Friendly Support Vector Machine. 4th International Workshop of Ambient Assisted Living, IWAAL 2012, Vitoria-Gasteiz, Spain, December 3-5, 2012. Proceedings. Lecture Notes in Computer Science 2012, pp 216-223.

Dataset:

Link:

https://www.kaggle.com/datasets/uciml/human-activity-recognition-with-smartphones/